Ecological Processes

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Quantifying the spatial and temporal distribution of tanglehead (*Heteropogon contortus*) on South Texas rangelands

Jose M. Mata, Humberto L. Perotto-Baldivieso[*], Fidel Hernández, Eric D. Grahmann, Sandra Rideout-Hanzak, John T. Edwards, Michael T. Page and Taylor M. Shedd

Abstract

Introduction: Tanglehead is a grass native to southwestern US rangelands; however, its prevalence as a native invasive on South Texas rangelands has increased rapidly during the last decade. Large areas of monotypic stands have emerged in Jim Hogg, Duval, Brooks, and Kleberg counties. The aim of this research is to understand the spatial and temporal dynamics of these invasions as a model for the assessment of native invasive species. Our specific objectives were to (1) evaluate the feasibility of classifying tanglehead using 1-m resolution imagery data, (2) assess the spatial and temporal distribution of tanglehead in relation to soil type and distance from roads, and (3) quantify the temporal and spatial distribution of tanglehead on our study sites. We combined remote sensing approaches with landscape metrics to quantify the spatial and temporal distribution of tanglehead in five locations across our study area. We calculated the normalized difference vegetation index and combined it with the original aerial imagery to conduct an unsupervised classification with the following land cover classes: woody vegetation, tanglehead, non-tanglehead herbaceous, and bare ground. Soil type and the distance from roads were assessed to determine the relationship between these factors and tanglehead spatial distribution.

Results: We were able to successfully map tanglehead using the 1-m imagery. Our image classification approach resulted in accuracies greater than 85% for all sites. Tanglehead occurred in sandy, loamy sand, and sandy loam soils. Over 70% of tanglehead cover occurred within the first 150 m from the edge of roads. This cover increased from 7.1% (SE = 1.1%) in 2008 to 17.8% (SE = 5.4%) in 2014. Once established, small patches of tanglehead began aggregating or coalescing with existing stands, thereby creating larger patches over larger areas.

Conclusions: Our study has shown the value of analyzing spatiotemporal dynamics of tanglehead with remote sensing techniques and landscape metrics to improve our understanding of establishment and dispersal processes of a native invasive. This study provides useful information to improve rangeland management decisions as well as assessing native invasive dynamics with potential applications for assessing its effects on wildlife habitat, livestock operations, and habitat restoration strategies.

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Introduction

Invasive plants pose a serious threat to native flora and fauna, often having effects that can be long term and irreversible once established across the landscape (Flanders et al. 2006). Invasives are capable of altering plant-community structure and composition, as well as ecosystem processes such as nutrient cycling and fire regimes (Fulbright et al. 2013). These changes can cause cascading effects on many species of wildlife as they rely on grasses and forbs for food, cover, and other resources essential to their survival. For example, areas in Australia that have been subjected to the invasion of gamba grass (*Andropogon gayanus* Kunth.), a high biomass producing perennial, have shown changes in fire regimes as well as reductions in soil nitrate availability, resulting in a reduction of native plant communities and wildlife abundance (Grice et al. 2013). Studies have shown that invasive grasses can significantly reduce the growth of long-lived native perennial forbs utilized by wildlife species (Williams and Crone 2006). In the USA, Flanders et al. (2006) observed that overall bird and arthropod abundance, as well as forb and grass species richness, was negatively impacted in areas dominated by invasive grasses.

Invasive species result from a number of factors, including habitat loss, fragmentation, disturbances, and climate change (e.g., Carey et al. 2012; Didham et al. 2007). Changes in climate patterns, in particular, can result in substantial changes to biodiversity, species ranges, and interactions with other species and their life histories (e.g., Hellmann et al. 2008; Mainka and Howard 2010). As a result, climate change, in conjunction with other aforementioned factors, can create shifts in distribution and abundance of invasive species (Kolb et al. 2002; Hoffmeister et al. 2005). These environmental and anthropogenic factors can also cause shifts within native communities and create opportunities for native species to increase in abundance or biomass in a landscape.

Traditionally, invasives are considered non-native or exotic species. However, native species within their natural ranges can have similar effects to those of invasive species. These species are defined as native invaders (Carey et al. 2012; Shackelford et al. 2013). There is growing consensus that native plants can act invasively and pose environmental threats similar to non-native or exotic species (Head and Muir 2004; Valéry et al. 2008). While there has been research conducted native invaders in salt marsh habitats (Minchinton 2012), little research has been conducted on the concept of native plants acting as invasives in rangelands, particularly in South Texas. As a result, the potential impacts that these species may have on communities of vegetation is unknown. Much of the research conducted on native invasives eludes to the possibility that, similar to non-native invasives, they may have negative effects on other native flora and fauna. The ability to quantify the spatial dynamics of native invasives could be key for the proper management of these species and could aid in the maintenance and restoration of native vegetative communities.

Remote sensing techniques have been widely used in vegetation mapping and spatial distribution assessment (Xu et al. 2013; Young and Sanchez-Azofeifa 2004). The use of remote sensing approaches provide the ability to monitor vegetation spanning large areas, analyze spatial dynamics, and offer long-term data analysis. These techniques are useful for classifying, delineating, and quantifying the spatial distribution of vegetation (Homer et al. 1993). Everitt et al. (1995) tested the feasibility of utilizing aerial photography and videography in North Dakota and Montana to distinguish leafy spurge (*Euphorbia esula* L. var. *esula*) from other plant species. In Colorado, remote sensing techniques have been used to stratify vegetation, providing the ability to distinguish scree slopes and snow beds (Frank and Thorn 1985). Anderson et al. (1993) used satellite imagery to detect and map false broomweed (*Ericameria austrotexana* Johnson.) in Texas, with the greatest accuracy occurring during drought conditions. These studies show that remote sensing techniques can be a viable option when monitoring the spatial and temporal distribution of a single species across large areas. The use of remote sensing data, in conjunction with landscape metrics and spatial analysis, can be very useful in understanding the spatial and temporal dynamics of the patterns of native invasives and their related ecological processes. This can be practical in landscapes where livestock and wildlife play an important role in influencing the patterns of vegetation and ecosystem function (Derner et al. 2009; Young et al. 2014) and may aid in better understanding the patterns of establishment by native invasives.

In this study, we analyzed the encroachment of tanglehead (*Heteropogon contortus* (L.) P. Beauv. ex Roem. & Schult.), a native invasive species, in South Texas. Tanglehead is a perennial bunchgrass native to Texas, northern Mexico, and much of the southwestern USA. It can also be found in Hawaii, Australia, and several African and European countries (Glendening 1941; Tjelmeland and Bryant 2010). Since at least 2000, this species has been expanding across South Texas rangelands, becoming a dominant species in plant communities within this region (Bielfelt and Litt 2016). Possible causes for the expansion of tanglehead may be related to an increase of milder winters and/or changes in rainfall regimes. The encroachment of tanglehead on rangelands is a cause for concern among ranchers and landowners as it may have negative effects on rangeland diversity as well as wildlife habitat (Tjelmeland and Bryant 2010). Unfortunately, little is known about the spatial extent and distribution of tanglehead in South Texas. Field monitoring for this species can be difficult due to the

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large spatial extent of its distribution. Thus, remote sensing could be useful in analyzing tanglehead and its dispersal.

There have been many studies conducted using remote sensing techniques to monitor vegetation successfully, but none have been applied to tanglehead. The aim of this research is to understand the spatial and temporal dynamics of tanglehead as a model for the assessment of native invasives. The specific objectives of this research are to (1) evaluate the feasibility of classifying tanglehead using the US National Agriculture Imagery Program (NAIP) imagery (hereafter "NAIP aerial imagery") data, (2) assess the spatial and temporal distribution of tanglehead in relation to soil type and distance from roads, and (3) quantify the temporal and spatial distribution of tanglehead on our study sites. To accomplish these objectives, we combined remote sensing data and techniques with spatial analysis and landscape metrics to describe and quantify the spatial and temporal distribution of tanglehead. We hypothesized that (1) the combination of the normalized difference vegetation index (NDVI) with red, green, blue, and near-infrared bands from aerial imagery would create a spectral signature unique to tanglehead, allowing it to be identified from other vegetation types; (2) soil texture (sandy soils) and roads (distance from roads) influenced the occurrence of tanglehead; and (3) the spatial and temporal dynamics of tanglehead dispersal could be quantified using a multi-temporal analysis.
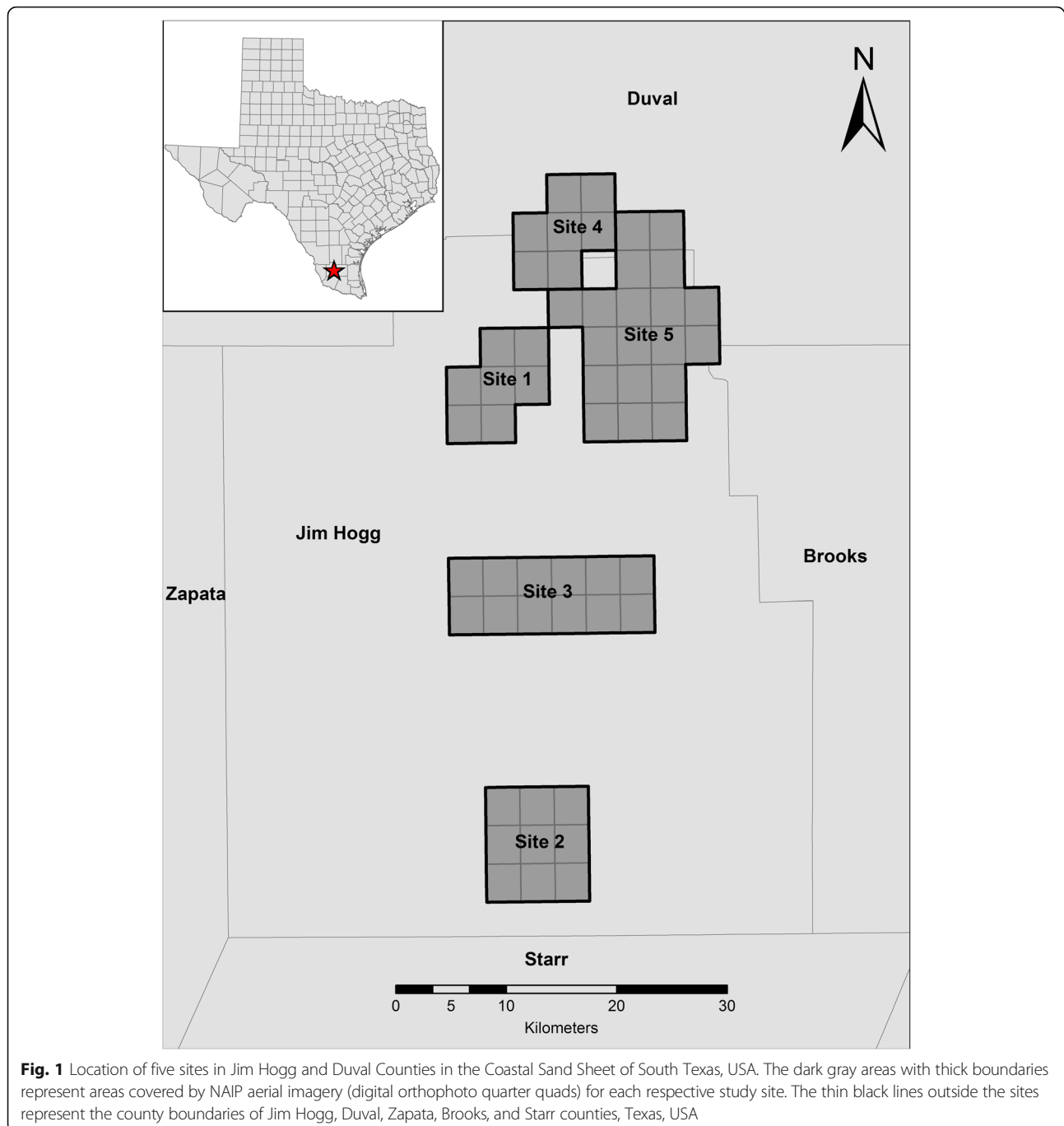
Methods
Study area
Our study was conducted on five sites with similar vegetation communities in Jim Hogg, and Duval Counties (Fig. 1) thanks to access provided by landowners. Site 1 had an area of 2529.7 ha; site 2, 6587.7 ha; site 3, 2736.7 ha; site 4, 3757.8 ha; and site 5, 6930.5 ha. The total area studied covered 22,542 ha, which corresponds approximately to 2.5% of the Coastal Sand Sheet subregion of South Texas (Texas Parks and Wildlife Department 2016a). The Coastal Sand Sheet subregion encompasses approximately 919,800 ha spread throughout Duval, Jim Hogg, Kenedy, Kleberg, Brooks, Willacy, Hidalgo, Jim Wells, and Starr Counties, and a small portion of Zapata County. Mean annual rainfall for this area of South Texas ranges from 500 to 800 mm (from Zapata to Kenedy Counties) (Texas Parks and Wildlife Department 2016b). Soil composition within the region ranges from deep sandy and coarse sandy soils to clay loam soils which support a mosaic of vegetation types. Live oak (*Quercus virginiana* Mill.) is scattered throughout the region along with honey mesquite (*Prosopis glandulosa* Torr.). Shrubs such as granjeno (*Celtis pallida* Torr.), brasil (*Condolia hookeri* M.C. Johnst.), black brush acacia (*Acacia rigidula* Benth.), and

catclaw acacia (*A. greggii* A. Gray var. *greggii*) are also widespread in the region. Grasslands in this region are dominated by fringed signalgrass (*Urochloa ciliatissima* (Buckley) R.Webster.), hooded windmillgrass (*Chloris cucullata* Bisch.), purple threeawn (*Aristida purpurea* Nutt.), Reverchon's bristlegrass (*Seteria reverchonii* (Vasey) Pilg.), and seascoast bluestem (*Schizachyrium scoparium* Nash E.P. Bicknell), a multitude of forbs including wooly (*Croton capitatus* Michx.) and northern crotons (*C. glandulosus* L.) and sand sunflower (*Helianthus debilis* Nutt.), and a variety of cacti such as Texas prickly pear (*Opuntia lindheimeri* Salm-Dyck ex Elgelm var. *lindheimeri* [Engelm.] Parfitt & Pinkava) and tasajillo (*O. leptocaulis* [D.C.] F.M. Knuth) (Everitt et al. 2002). This subregion has experienced increasing prevalence of tanglehead since the 1990s (Texas Parks and Wildlife Department 2016a; Wester et al. 2017). The prevalence of sandy soils and high temperatures in this area provides excellent conditions conducive for the growth of tanglehead (Tothill 1977).

Data collection and analyses
We used NAIP aerial imagery from the United States Department of Agriculture Farm Service Agency. This aerial imagery is periodically acquired during the agricultural growing season in the continental USA (United States Department of Agriculture 2015). We downloaded NAIP aerial imagery (1-m resolution, natural color, and color-infrared digital orthophoto quarter quads) of the study sites for the years of 2008, 2010, 2012, and 2014 through the Texas Natural Resources Information System (TNRIS) (http://tnris.org/) because these years have all the required bands (red, green, blue, and near-infrared bands) for our analysis. Available imagery from previous years is in black and white or color infrared (red, green, and near-infrared bands), which did not allow us to perform the methodology developed in this research. We developed a NDVI layer in ERDAS Imagine 2015 (Hexagon Geospatial) and then combined it with the original NAIP aerial imagery bands (red, green, blue, near infrared) using the layer stack function in ERDAS Imagine 2015 (Perotto-Baldivieso et al. 2009). We used NDVI as a measure of vegetation "greenness" to identify the spectral signature of tanglehead. Photosynthetic activity influences the NDVI values, increasing as "greenness" or photosynthetic activity increases in a living plant (Burgan and Hartford 1993). This allows vegetation to be more easily distinguishable from other cover types (Pettorelli et al. 2005). The combined images (NAIP bands + NDVI band) were classified using an unsupervised classification method (Xie et al. 2008; Perotto-Baldivieso et al. 2009). This method is based on an Iterative Self-Organizing Data Analyses Technique

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Fig. 1 Location of five sites in Jim Hogg and Duval Counties in the Coastal Sand Sheet of South Texas, USA. The dark gray areas with thick boundaries represent areas covered by NAIP aerial imagery (digital orthophoto quarter quads) for each respective study site. The thin black lines outside the sites represent the county boundaries of Jim Hogg, Duval, Zapata, Brooks, and Starr counties, Texas, USA

Algorithm (ISODATA) which recalculates the statistics of each image after each iteration until the defined number of iterations has been met and/or until a percent convergence threshold (95%) has been reached. The output image was reclassified as woody vegetation, tanglehead, non-tanglehead herbaceous, and bare ground.

Our goal was to achieve an overall image accuracy of 85% accurate or greater (Jensen 1995). This was determined by first conducting an initial desk accuracy assessment. The purpose of this assessment was to review

the classification against the original NAIP aerial imagery prior to going to the field. We generated 200 random points per image in ArcMap 10.5 (ESRI; Redlands, CA) and compared visual observation and image classification for each point. We then calculated an overall accuracy assessment using a confusion matrix (Congalton 1991; Foody 2009). If the overall accuracies were < 85%, classified image(s) were reviewed and reclassified. We repeated this process until an accuracy of ≥ 85% was obtained for each individual image. Secondly, field data for each of the

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classified cover types were collected using 1–2 m accuracy hand-held GPS units (Trimble Juno 5). A total of 1423 field points were collected (Table 1). We collected points for each cover class following the road network and randomly selected sampling areas that were at least 800 m apart. At each sampling area, we randomly collected between 5 and 10 points in a 300 m radius from the sampling area. Once the image classification protocol met an 85% accuracy or more, we repeated the image classification process for 2008, 2010, and 2012. Once the images met accuracy standards, we used the classified imagery to assess the spatial and temporal distribution of tanglehead in relation to soil type, distance from roads, as well as quantifying the amount and spatial distribution of tanglehead in our study sites.

We derived soil data for Jim Hogg and Duval Counties from the soil survey geographic database (SSURGO) to analyze the presence of tanglehead in relation to soil textural class (Natural Resources Conservation Service 2017). We grouped soils for each county into one of 12 soil textural classes based on the soil texture triangle (National Agriculture Institute 2015). Textural classes found on the study sites were clay, clay loam, loam, loamy sand, sand, sandy clay loam, and sandy loam. We used zonal statistics in ArcGIS (ESRI; Redlands, CA) to quantify tanglehead cover within each textural class for each study site.

Roads and infrastructure were digitized at a cartographic scale of 1:1500 from the NAIP aerial imagery. We used the Euclidean distance analysis to quantify presence of tanglehead cover in relation to the distance from the roads. This spatial analysis measures the distance from the roads to the center of each pixel in the raster layer. We assessed distance from roads by grouping pixels with tanglehead in 25-m bins and calculated frequency distribution (%) for each bin and each year.

We quantified the spatial structure and temporal changes of tanglehead across the landscape using class level landscape metrics (Fragstats 4.2; McGarigal et al. 2012) for tanglehead. These metrics were percentage cover (PLAND; %), mean patch area (MPA; ha), patch density (PD; number of patches/100 ha), mean shape index (MSI), largest patch index (LPI; %), aggregation index (AI), and edge density (ED; m/ha) (Perotto-Baldivieso et al. 2011; Young et al. 2014; Zemanova et al. 2017). We used PLAND to measure the overall changes in tanglehead cover present in the landscape. PD and MPA describe the number and size of patches of tanglehead. ED quantifies the amount of edge per unit area, and LPI provides a percentage of the area covered by the largest patch of tanglehead in the landscape. We measured the aggregation or lumping of patches using AI and patch complexity with MSI. We compared landscape metrics between years using a Kruskal–Wallis one-way variance analysis with a significance level of 0.05 due to unequal variances and non-normal distributions (Dickins et al. 2013).

Results

The combination of the NDVI and original bands yielded image classifications that exceeded $\geq 85\%$ overall accuracy across all five sites: 86.1% (site 1), 85.4% (site 2), 89.5% (site 3), 88.2% (site 4), and 85.6% (site 5) (Table 1). The greatest percentages of tanglehead cover in 2014 occurred in sandy soils (mean = 20.1%; SE = 6.2) followed by loamy sand (mean = 16.3%; SE = 5.6) and sandy loam (mean = 15.3%; SE = 5.6) soils. The presence of tanglehead cover increased (Table 2) in loamy sand ($X^2 = 9.2$, $P < 0.05$, Fig. 2a), sand ($X^2 = 10.2$, $P < 0.05$, Fig. 2b), and sandy loam ($X^2 = 7.5$, $P < 0.10$, Fig. 2c) soil textural classes between 2008 and 2014. We did not observe tanglehead cover in other textural classes across the study site. The Euclidean distance analysis values show that the greatest amounts of tanglehead cover occurred within the first 150 m from the roads (Fig. 3). Overall percent tanglehead cover increased ($P < 0.01$) from 7.1% (SE = 1.1) in 2008 to 17.8% (SE = 5.4) in 2014 (Fig. 4a). Values for MPA increased ($P < 0.01$) from 5 m^2 (SE = 0.7) in 2008 to 14 m^2 (SE = 6.8) in 2014 (Fig. 4b).

Table 1 The number of points collected to determine classification accuracy of tanglehead (*Heteropogon contortus*) at five study sites in Jim Hogg and Duval Counties, Texas, USA

Site number	Number of points	Accuracy (%)
Site 1	108	86.1
Site 2	508	85.4
Site 3	286	89.5
Site 4	237	88.2
Site 5	284	85.6
	Total 1423	Mean 86.9

Table 2 Results of the Kruskal–Wallis one-way variance analysis for landscape metrics and soil textural classes

Metric	X^2	P value
PLAND	11.9	0.008
PD	13.5	0.004
LPI	7.3	0.063
ED	13.6	0.003
MPA	11.9	0.008
MSI	7.8	0.049
AI	12.3	0.006
Soil textural class		
Loamy sand	9.2	0.027
Sand	10.2	0.017
Sandy loam	7.5	0.059

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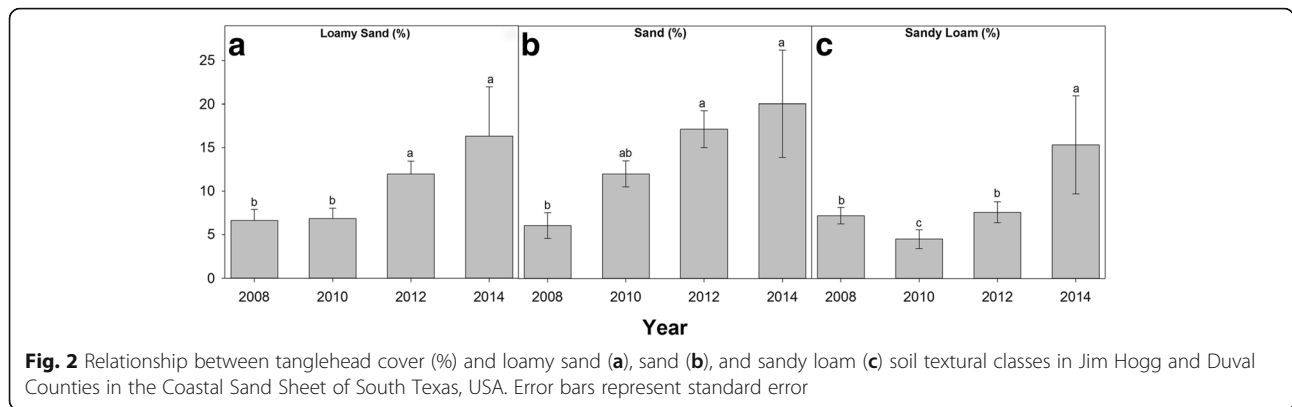
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Fig. 2 Relationship between tanglehead cover (%) and loamy sand (**a**), sand (**b**), and sandy loam (**c**) soil textural classes in Jim Hogg and Duval Counties in the Coastal Sand Sheet of South Texas, USA. Error bars represent standard error

Values of PD decreased ($P < 0.01$) from 2008 (mean = 15,449.4 patches/100 ha; SE = 1672.5) to 2010 (mean = 6011.3 patches/100 ha; SE = 749.4). This is probably due to small patches coalescing as tanglehead cover increases. However, PD values increased in 2012 (mean = 10,349.9 patches/100 ha; SE = 639.8) and 2014 (mean = 16,444.6 patches/100 ha; SE = 1769.7) (Fig. 4c). Values for MSI were similar across years ($X^2 = 7.9$, $P = 0.05$, Fig. 4d). Largest patch index values increased from 0.1 ha (SE = 0.03) in 2008 to 0.4 ha (SE = 0.2) in 2014 (Fig. 4e). In 2008, AI values were higher than 2010 and 2012, but similar to 2014 ($X^2 = 12.3$, $P < 0.01$, Fig. 4f). Values for ED decreased from 2008 (mean = 1608.5 m/ha; SE = 203.3) to 2010 (mean = 1007.6 m/ha; SE = 98.2) and then increased in 2012 (mean = 1628.0 m/ha; SE = 94.2) and 2014 (mean = 2637.7 m/ha; SE = 347.2) (Fig. 4g).

Discussion

One-meter resolution NAIP aerial imagery merged with the NDVI band proved successful in identifying tanglehead from other vegetation types. To our knowledge, this is the first study that has used this approach to monitor tanglehead over large areas. Perotto-Baldivieso et al. (2009) used similar approaches to assess small patches of depression forests in tropical environments. The accuracy (> 85% accuracy) of this methodology in

both studies provides justification for expanding the use of this approach to other areas and potentially to assess other species. This technique can prove to be an effective tool for managing and studying native invasives over large areas with potential applications in wildlife and livestock management. However, it is also important to highlight that these methods can have some limitations in terms of spatial, spectral, and temporal resolution. In our study, given the speed of tanglehead expansion, the NAIP aerial imagery used was high in spatial resolution (1 m), but low in spectral (four bands: red, green, blue, and near infrared) and temporal resolution (every 2 years). The use of NDVI merged with the NAIP bands improved the spectral resolution by adding information related to vegetation "greenness" across the study area. Temporal resolution could potentially be improved with LANDSAT imagery (30 m) which is collected every 16 days (Roy et al. 2014). The use of LANDSAT for tanglehead studies still needs to be explored, as cloud cover can limit the image availability for our study area. Spatial resolution can also limit the ability to accurately identify tanglehead within our study area. The MPA values recorded for tanglehead were 0.0041 ha (41 m^2), and the pixel resolution for LANDSAT is 0.09 ha (900 m^2). Future research should explore the fusion
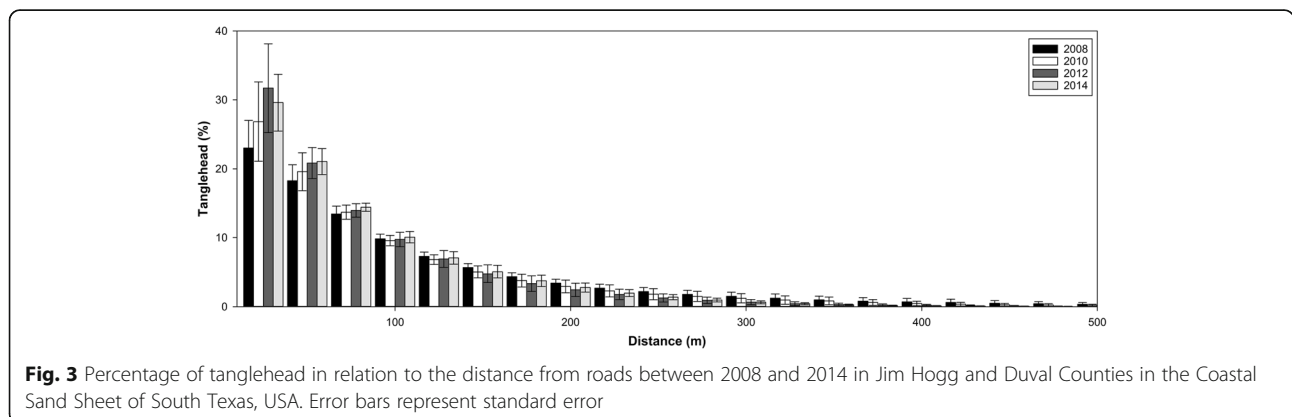

Fig. 3 Percentage of tanglehead in relation to the distance from roads between 2008 and 2014 in Jim Hogg and Duval Counties in the Coastal Sand Sheet of South Texas, USA. Error bars represent standard error
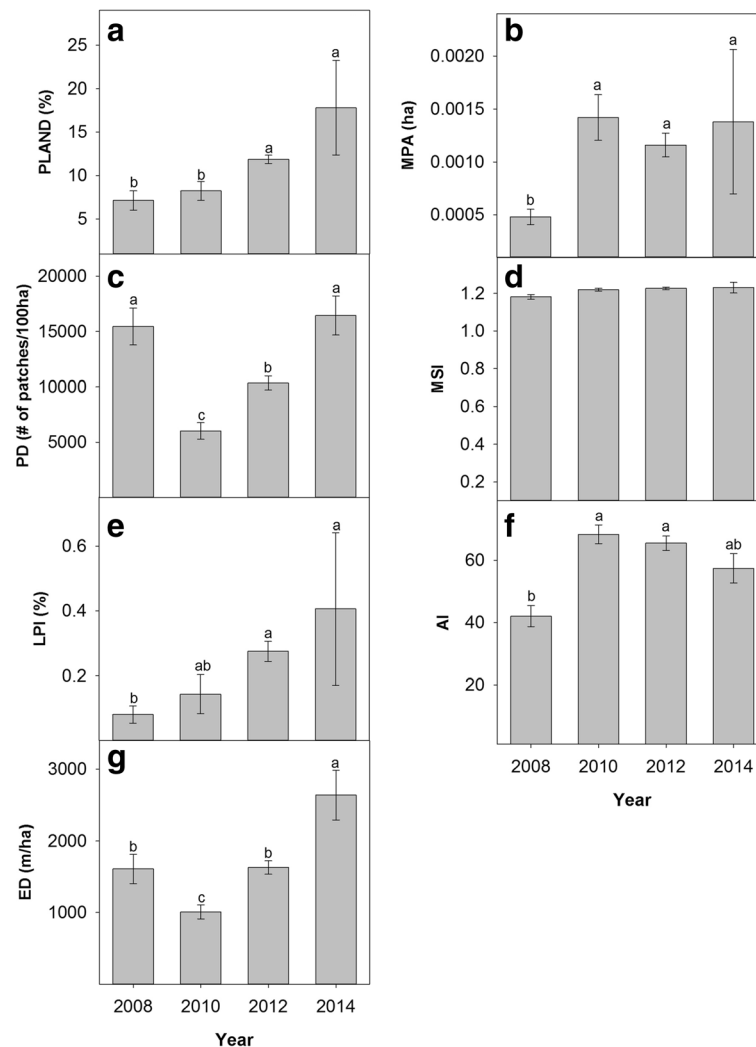
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Fig. 4 Landscape metrics describing the spatial structure of tanglehead in the five study sites in South Texas: percentage cover (**a**), mean patch area (**b**), patch density (**c**), mean shape index (**d**), largest patch index (**e**), aggregation index (**f**), and edge density (**g**). Error bars represent standard error

of lower spatial resolution and higher spectral and temporal resolution platforms for the monitoring of tanglehead. Most available high spectral resolution sensors acquire data with a relatively coarse spatial resolution, limiting their applications in areas where vegetation appears in small patches (Zhang 2015). Image fusion combines images from different platforms with minimal loss of the original data, potentially providing a balance between temporal, spectral, and spatial resolution for image classification (Amarsaikhan et al. 2011; Zhang 2010). Additionally, the use of unmanned aerial systems could deliver very high-resolution imagery for monitoring native invasives. Unmanned aerial systems provide rapid acquisition of ultrahigh spatial resolution data at relatively low cost and can be used to sample areas and identify native invasive communities over large areas before image classification begins. This field of remote sensing could be a valuable

tool in the mapping and detection of native invasives in the near future (Mafanya et al. 2017).

The use of remote sensing combined with spatial analysis and landscape metrics was the key in quantifying the spatial and temporal dynamics of tanglehead spread in the landscape between 2008 and 2014. We found that the greatest percentage of tanglehead cover occurred near roads (150 m) in soils with sandy texture. As new patches of tanglehead appeared in the landscape (increased PD), existing patches as well as the new patches coalesced, forming larger stands covering larger areas (increased PLAND, LPI, ED, MPA, and AI between 2008 and 2014). Landscape metrics were the key in identifying the spatial patterns that helped us understand the spread of tanglehead at the landscape level. Young et al. (2014) found that the use of spatial data derived from remote sensing, combined with

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landscape metrics, was valuable for assessing vegetation patterns and their related ecological processes.

Though specific mechanisms of dispersal were not studied, the Euclidean distance analysis results suggest that roads may play an important role in the dispersal of tanglehead. Roads are known to be a dispersal mechanism by humans, livestock, and wildlife (Wichmann et al. 2009). We hypothesize that tanglehead first establishes near roads and that vehicles collect seeds in the tires or on the body of the vehicle and disperse them over great distances (Auffret and Cousins 2013). Roads also act as a corridor utilized by livestock and wildlife, allowing them to freely move through the landscape. Livestock and wildlife can disperse seeds that are partly edible or that may be attached to them (Planchuelo et al. 2016). As a result, livestock and wildlife could be potential vectors by which native invasive species spread. Future research should emphasize on tanglehead response to changes winter temperatures and precipitation as a model to evaluate the impact of climate fluctuation to native invasive species communities.

Conclusions

Our study has shown the value of analyzing spatial and temporal dynamics of tanglehead with remote sensing techniques, spatial analysis, and landscape metrics to improve our understanding of establishment and dispersal processes of a native invasive. Our research specifically sought to validate the feasibility of classifying tanglehead and quantifying its spatial and temporal distribution in the western South Texas Sand Sheet as an example to monitor the invasion of individual species. Field monitoring of a vegetative species can be extremely expensive and time intensive and is dependent upon landowner cooperation to be successful. The ability to remotely analyze vegetation can provide opportunities to evaluate large areas at minimal cost and aid in understanding dispersal processes of native invasives. The approach taken in this study generates information about the distribution and dispersal of a native invasive species and could potentially be used to help make management decisions and develop monitoring programs to control and reduce the expansion of native invasives. The approaches from this study also have the potential to be utilized to assess and quantify the effects of native invasive species on wildlife habitat, livestock operations, and restoration strategies.

Abbreviations

AI: Aggregation index; CIR: Color infrared; ED: Edge density; ISODATA: Iterative Self-Organizing Data Analysis Technique Algorithm; LPI: Largest patch index; MPA: Mean patch area; MSI: Mean shape index; NAIP: National Agriculture Imagery Program; NDVI: Normalized difference vegetation index; PD: Patch density; PLAND: Percentage of vegetation cover; SSURGO: Soil survey geographic database; TNRIS: Texas Natural Resources Information System

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